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Smart camera traps and computer vision improve detections of small fauna

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Abstract

Limited data on species' distributions are common for small animals, impeding conservation and management. Small animals, especially ectothermic taxa, are often difficult to detect, and therefore require increased time and resources to survey effectively. The rise of conservation technology has enabled researchers to monitor animals in a range of ecosystems and for longer periods than traditional methods (e.g., live trapping), increasing the quality of data and the cost-effectiveness of wildlife monitoring practices. We used DeakinCams, custom-built smart camera traps, to address three aims: (1) To survey small animals, including ectotherms, and evaluate the performance of a customized computer vision object detector trained on the SAWIT dataset for automating object classification; (2) At the same field sites and using commercially available camera traps, we evaluated how well MegaDetector—a freely available object detection model—detected images containing animals; and (3) we evaluated the complementarity of these two different approaches to wildlife monitoring. We collected 85,870 videos from the DeakinCams and 50,888 images from the commercial cameras. For object detection with DeakinCams data, SAWIT yielded 98% Precision but 47% recall, and for species classification, SAWIT performance varied by taxa, with 0% Precision and Recall for birds and 26% Precision and 14% Recall for spiders. For object detections with camera trap images, MegaDetector returned 99% Precision and 98% Recall. We found that only the DeakinCams detected nocturnal ectotherms and invertebrates. Making use of more diverse datasets for training models as well as advances in machine learning will likely improve the performance of models like YOLO in novel environments. Our results support the need for continued cross-disciplinary collaboration to ensure that large environmental

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datasets are available to train and test existing and emerging machine learning algorithms.

KEYWORDS
artificial intelligence, camera traps, computer vision, conservation technology, herpetofauna, invertebrates, machine learning, wildlife survey

INTRODUCTION

The biodiversity crisis is accelerating with global environmental change (Barnosky et al., 2011), and technological advances are required to collect the information necessary to diagnose issues and aid solutions (Hahn et al., 2022; Kerry et al., 2022). This is particularly the case for species that are data deficient (Garcia-Rosello et al., 2023; Wotherspoon et al., 2024) or are difficult, time-consuming, or costly to monitor with traditional methods, such as cryptic, small-bodied, or rare taxa (Hoye et al., 2021; Welbourne et al., 2015). There are well-known taxonomic biases in biodiversity research that inevitably lead to large gaps in our understanding of species' extinction risks (Davies et al., 2018; dos Santos et al., 2020). Invertebrates and herpetofauna are diverse groups that are poorly known relative to other groups, such as birds and large mammals (Marco et al., 2017; Titley et al., 2017). With over a million species at risk of extinction (IPBES, 2019), researchers are increasingly turning to advances in technology to address such knowledge gaps (Allan et al., 2018; Farley et al., 2018).

Camera trapping is now a standard, cost-effective monitoring tool for surveying wildlife globally (Blount et al., 2021; Bruce et al., 2025; Kerry et al., 2022). Camera traps allow for longer survey periods while minimizing time spent in the field and the repeated disturbance to field sites commonly associated with live trapping (De Bondi et al., 2010; Welbourne et al., 2015). Passive monitoring with camera traps also has animal welfare benefits by avoiding the live capture of animals (Dundas et al., 2019). The data obtained, in the form of still images or videos, have been used for biodiversity inventory (Ahumada et al., 2013; Steinbeiser et al., 2019), to estimate species' abundance and/or occupancy (Cove et al., 2013; Moeller et al., 2018), monitoring cryptic or threatened species' populations (Barber-Meyer & Newsome, 2022; Linkie et al., 2013), and observing species interactions or behaviors (Chan et al., 2023; Steinmetz et al., 2013).

A common issue with camera trapping is the generation of false triggers, that is, images that do not contain animals (Greenberg & Godin, 2015). This leads to early exhaustion of camera batteries and memory cards, very large datasets, and lengthy delays in data processing and analysis (Chalmers et al., 2023; Fennell et al., 2022). Camera traps therefore create challenges for researchers through the large volumes of data collected, the limited time, budget, and expertise available to process the data, and storage requirements (Chalmers et al., 2023; Young et al., 2018). Furthermore, because most commercial camera traps use heat-in-motion passive infrared sensors, smaller animals, particularly ectotherms, are more difficult to detect (Corva et al., 2022; Richardson et al., 2017). Indeed, Ahumada et al. (2019) and Nguyen et al. (2023) highlight that many camera trap datasets are dominated by medium-to-large mammals and birds, introducing taxonomic bias into ecological studies. This is also reflected in the dominance of mammals in camera trap studies (Delisle et al., 2021). This can lead to management decisions being made using a narrow selection of easy-to-survey taxa. Some of these challenges can be addressed through appropriate experimental design. For example, changing the orientation and layout of camera trap arrays to detect species of interest (Moore et al., 2020; Nichols et al., 2017). Using video capture can also improve the detection of ectotherms (Swinbourne et al., 2018; Swinnen et al., 2014), although the benefits may be lost if the camera trap model relies on passive infrared detection.

To address some of these issues, Corva et al. (2022) developed a custom-built smart camera trap specifically for small ectothermic fauna and fast-moving small endotherms like small mammals. These smart traps ("DeakinCams" hereafter) were designed to use machine vision, a form of artificial intelligence, to detect motion across the camera's field of view (Corva et al., 2022). Machine vision has emerged as a powerful tool for automating, partially or in full, the processing of large ecological datasets such as those generated by camera traps (Farley et al., 2018; Norouzzadeh et al., 2018). DeakinCams continuously monitor video footage from their inbuilt cameras using a single-board computer, which applies a foreground detection algorithm to identify pixel changes in image sequences from the video footage (Corva et al., 2022). A recording is saved when movement is detected within it (Corva et al., 2022). These recordings are collected at the end of DeakinCams

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deployment for processing through a post-capture machine learning tool. Using artificial intelligence at the point of capture has the potential to limit the volume of empty images.

Many post-capture machine learning tools are available to process camera trap images and videos (Ahumada et al., 2019; Beery et al., 2018). Deep learning computer vision uses image recognition to detect and classify objects in an image (Chen et al., 2014), leading to greater efficiency in research projects (Fennell et al., 2022; Vélez et al., 2022). However, the performance of computer vision models relies on large training datasets of annotated images or objects (Nguyen et al., 2023). Further, the reproducibility of results in images with different background scenes remains a challenge due to the training data used (Beery et al., 2018; Zhou et al., 2023). This has led to a range of customized models (Vélez et al., 2022) that rely on varying levels of technical expertise or expensive hardware to run (Penn et al., 2023). This can put artificial intelligence out of reach for general users (Desprez et al., 2023; Vélez et al., 2022). In contrast, large-scale collaborations with extensive training data from numerous camera trapping studies have enabled the development of more generalizable machine-learning tools such as MegaDetector (Microsoft AI for Earth, 2018). However, the datasets used to train such models are often imbalanced in terms of their taxonomic resolution (Nguyen et al., 2023) and therefore require further field testing.

In remote field settings, using DeakinCams may expand the diversity of fauna being monitored. This is particularly vital in places where current monitoring approaches primarily focus on birds and mammals. We deployed the DeakinCams in a semi-arid landscape in western Victoria, Australia. Our study provides a proof-of-concept assessment of the DeakinCams for use in terrestrial wildlife surveys and an assessment of computer vision object identifiers. We aimed to: (1) evaluate the performance of a computer vision algorithm, YOLOv5 (Redmon & Farhadi, 2017), trained on the DeakinCams SAWIT dataset (Nguyen et al., 2023) for detecting animals in a new DeakinCams dataset and classifying them into broad taxonomic groups; (2) assess the ability of a freely available model, MegaDetector (Microsoft AI for Earth, 2018), trained on camera trap images from many different datasets (Beery, Morris, & Yang, 2019) to detect animals from a dataset collected with Reconyx camera traps at the same DeakinCams sites. Finally, (3) we aimed to evaluate the complementarity of the DeakinCam and Reconyx camera trap approaches to wildlife surveys in terms of the taxonomic groups detected and the capacity to automate initial data labeling of these different camera systems.

METHODS

Study area

This study was conducted on Wotjobaluk country in the Wimmera district of central west Victoria in southeastern Australia (Figure 1). This landscape is at the southernmost extent of the Mediterranean-type climate in southeastern Australia (Clarke et al., 2021; Keeley et al., 2011). We used 18 sites from a broader study investigating the effects of fire history on wildlife (Pestell, 2024a, 2024b), allowing us to access the Reconyx camera trap images collected from that study to assess alongside the DeakinCams. Fifteen sites were in Little Desert National Park and three in Mount Arapiles—Tooan State Park, in Victoria, Australia. To maintain consistency across the study area, all sites were in semi-arid treeless heathland dominated by shrubs such as *Leptospermum myrsinoides* and *Allocasuarina mackliniana* (McIntosh et al., 2023). Sites were established at least 100 m from management tracks, away from ecotones, and separated by a minimum of 1 km.

SAWIT with DeakinCams

DeakinCams were deployed in pairs, 100 m apart, at each site from 5 December 2019 to 22 January 2020 (Appendix S1: Figure S1). Each DeakinCam was secured to a metal post 30 cm above the ground, facing downwards to detect small fauna, and angled at approximately 15° to avoid the post being within the field of view. A plastic drift fence was installed 5 m to either side of the DeakinCams to direct small fauna through the opening for video capture (Figure 2). The DeakinCams were powered by a separate, solar-powered battery (Corva et al., 2022). We programmed the foreground detection algorithm, a Gaussian mixture model for background subtraction (Zivkovic & van der Heijden, 2006), on board the DeakinCams to be highly sensitive to movement (minimum 1 cm^2 of changing pixels) to ensure small fauna would be detected (Nguyen et al., 2023).

The DeakinCams suffered some technical issues during the deployment. Seven (19%) of the 36 units did not work at all during the deployment period, and 22 (79%) captured 66 video segments before no longer taking videos (see Corva et al. (2022) for specific fault details). This meant that the DeakinCams were not working for the entirety of the survey period, so they likely missed detections. Two pairs of DeakinCams did not work at all during the deployment, so the paired Reconyx camera trap data from these two sites were also removed from analysis.

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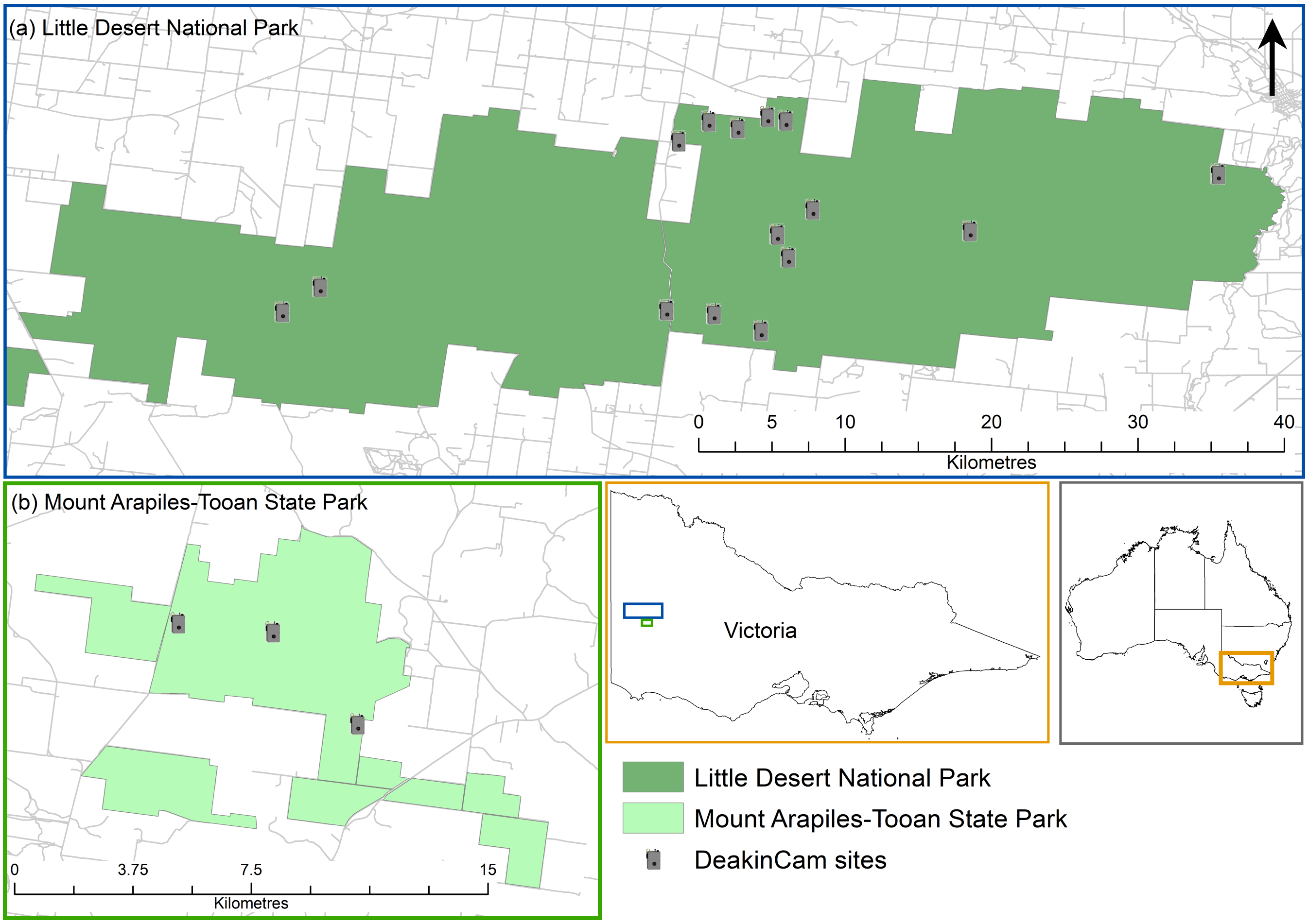

FIGURE 1 Maps of the study area, showing the study sites (camera icon) in (a) Little Desert National Park and (b) Mount Arapiles—Tooan State Park, Victoria, Australia.

To manually classify DeakinCams videos, we used the program Timelapse (Greenberg & Godin, 2015). Timelapse is an image management program designed for manually processing camera trap images and videos (Greenberg & Godin, 2015). All videos of vertebrates were classified to species and invertebrates were classified to order. All manual classifications were performed by RDS to maintain consistency across sites and camera trap types (Zett et al., 2022). We used the SAWIT model (Nguyen et al., 2023) to process all video segments obtained during field deployment, using the same code and confidence threshold (0.25) used in Nguyen et al. (2023) to enable general comparison with that study. The SAWIT dataset was collected in a temperate dry forest in central Victoria, experiencing milder environmental conditions than our study area, but sharing similar mammal and reptile fauna (Nguyen et al., 2023). For example, mammals such as the short-beaked echidna (*Tachyglossus aculeatus acanthion*), black wallaby (*Wallabia bicolor*), and silky mouse (*Pseudomys apodemoides*) as well as reptiles of the *Cristinus*, *Ctenotus*, and *Pseudonaja* genera, occur in both study areas (Robertson & Coventry, 2019). We therefore retained all animal categories defined for the SAWIT dataset (*bird, big mammal, frog, scorpion, small mammal, snake*, and *spider*; Nguyen et al. (2023)) and manually changed *lizard* to *large reptile* and *small reptile* categories to distinguish the sizes of reptiles being detected. The SAWIT model was run in Pytorch 1.1 (Paszke et al., 2019) on 2 NVIDIA GeForce RTX2080Ti GPUs. Because the SAWIT model performs both object detection and object classification, we first validated the outputs as correct or incorrect detection and then correct or incorrect classification.

MegaDetector with Reconyx camera traps

Two Reconyx camera traps were deployed 100 m apart at each site (Appendix S1: Figure S1), one white flash (Reconyx H550) and one infrared-illuminated (Reconyx H500), with a scent lure at each camera to increase detection rates (Rendall et al., 2021). Each Reconyx camera

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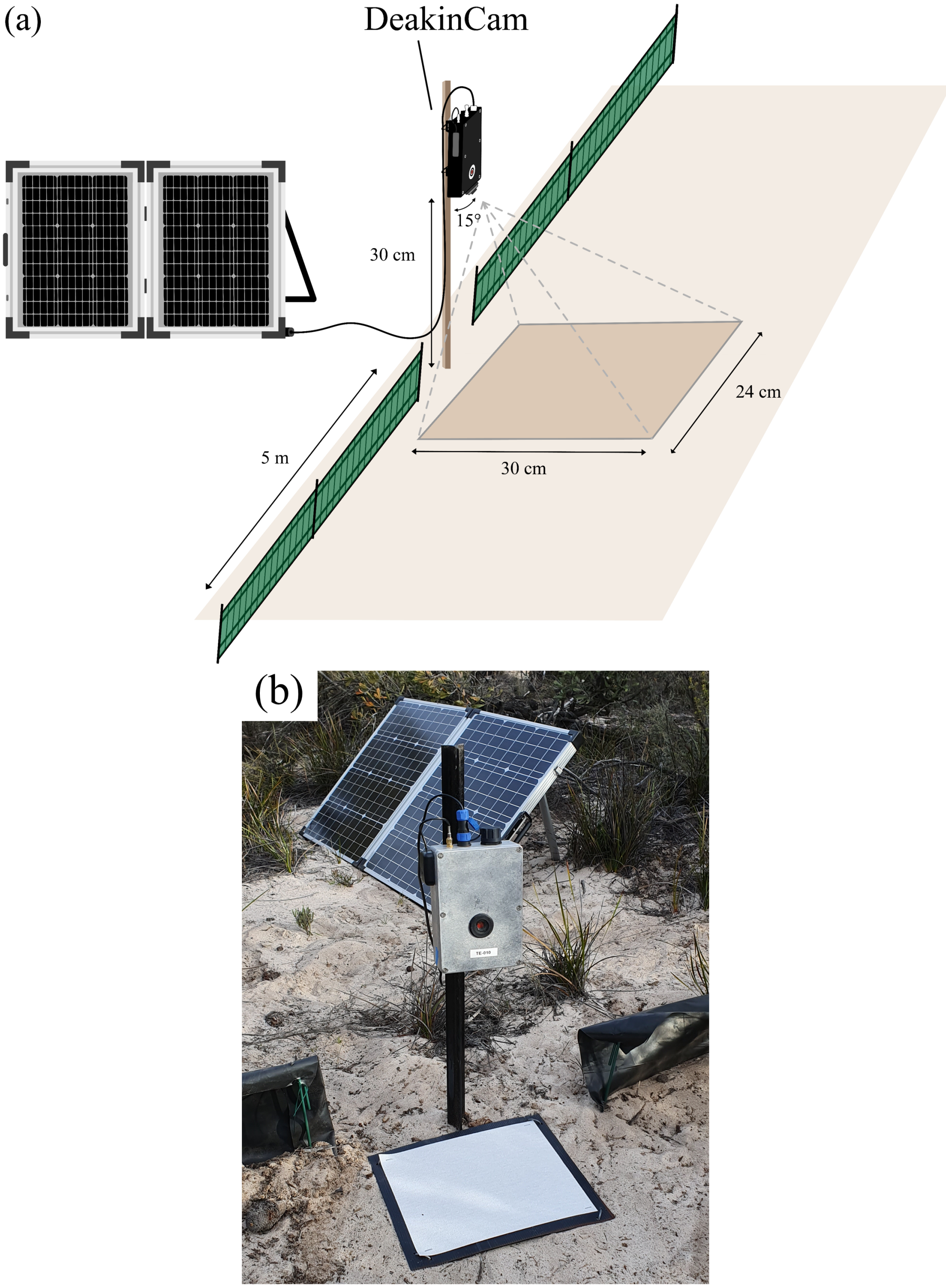

FIGURE 2 (a) DeakinCam site setup showing mounting position, drift fence, and solar panel placement (not to scale), and (b) in-field deployment, Little Desert National Park, Australia. Photo credit: A. Pestell.

trap was mounted on a wooden stake 50 cm above the ground with an outward-facing orientation and angled slightly so that the base of a baited lure station was centered in the field of view. The Reconyx H550 camera trap was used to detect small fauna. The lure station was placed 1.7 m from the camera trap, and a bait canister containing a mixture of rolled oats, peanut butter, and golden syrup was mounted on a wooden stake at a height of 40 cm above the ground. The Reconyx H500 camera trap was used to detect larger fauna. Each lure station was placed 3 m away, and a baited canister with a mixture of blood and bone and tuna oil was mounted at 90 cm above the ground on a wooden stake. Both Reconyx camera traps were set to take a sequence of five

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consecutive photographs per trigger with no interval between triggers.

We used the program Camelot (Hendry & Mann, 2018) to manually classify the Reconyx camera trap images. As with videos, all manual processing was completed by RDS for consistency. Once manually classified, the Reconyx camera trap images were batch processed through MegaDetector version 5a (hereafter "Megadetector"; Microsoft AI for Earth, 2018) on an NVIDIA GeForce GTX 1660 Ti GPU, using the default code and confidence threshold (0.20) to generate recognition outputs. MegaDetector recognition outputs provide the object type (Animal, Person, or Vehicle), bounding box coordinates for the objects, and a confidence value for each recognition (Beery, Morris, & Yang, 2019). Timelapse has in-built functionality to read the MegaDetector recognition outputs and display the results (Greenberg, 2025). We, therefore, imported these outputs into Timelapse to enable a comparison with the manually classified data. We chose not to perform a post-processing step designed to remove multiple detections of stationary objects because the SAWIT model does not use a comparable function.

To validate the MegaDetector recognition data, we followed the Timelapse documentation (Greenberg, 2025) and set the "Use recognition" query in Timelapse to "All." We then recorded the object type, as well as four categories that captured potential recognition errors (Figure 3). These categories represented false negatives (type II error; Figure 3a) where MegaDetector did not detect an object that was present, and false positives (type I error; Figure 3b), where MegaDetector either wrongly assigned an object type to an empty image or assigned the wrong object type (e.g., Animal as Person). The remaining two categories accounted for instances where MegaDetector correctly detected an object, but the count

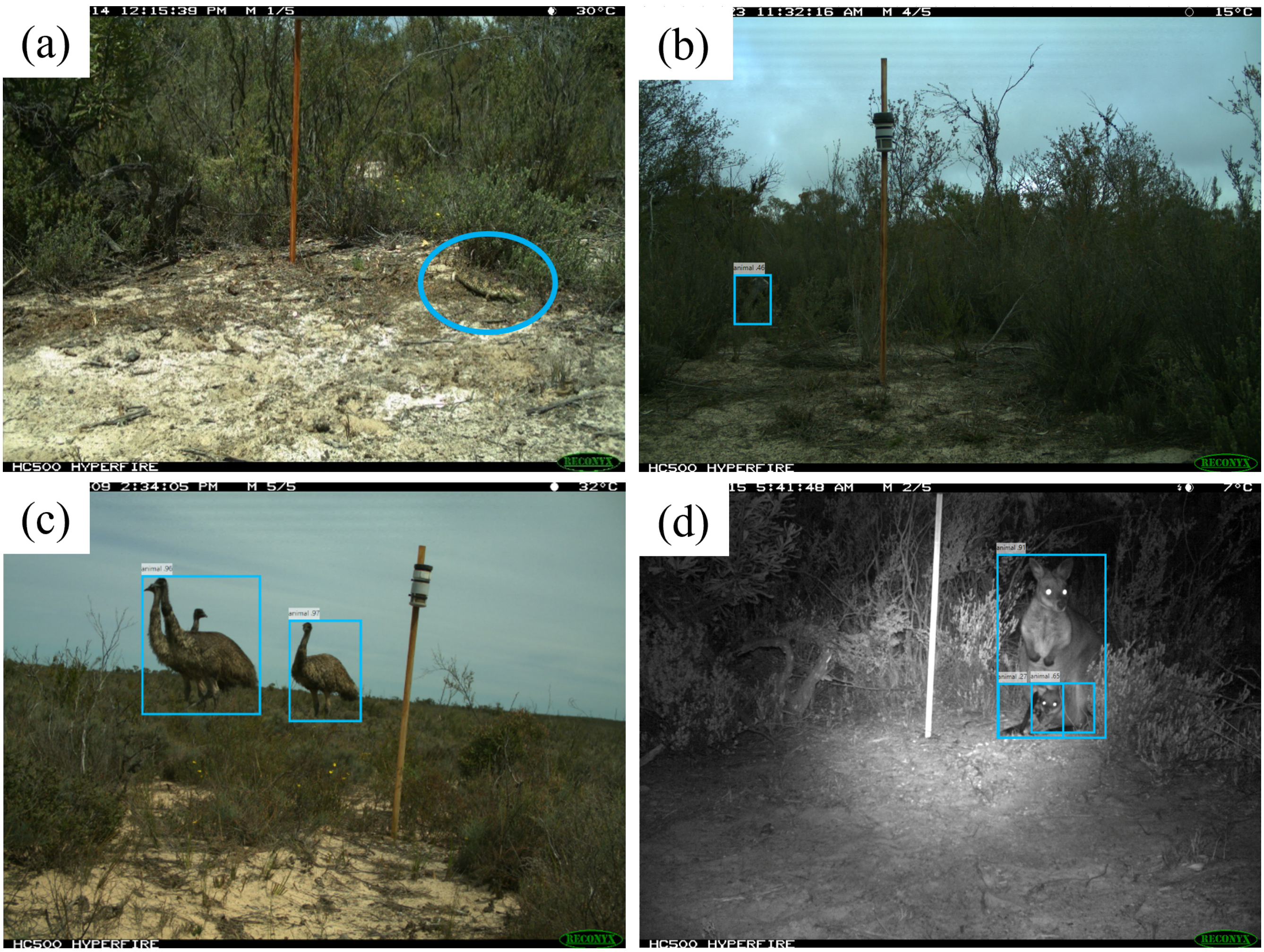

FIGURE 3 Examples of error categories recorded during MegaDetector validation of the Reconyx camera trap data: (a) False negative of a shingleback lizard (*Tiliqua rugosa*) missed by MegaDetector; (b) False positive of vegetation marked as an animal by MegaDetector; (c) Undercount of emu (*Dromaius novaehollandiae*) recognized by MegaDetector; and (d) Overcount of black wallaby (*Wallabia bicolor*) recognized by Megadetector. Photo credits: A. Pestell.

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of the object/s, as indicated by the number of bounding boxes in an image, was either too few (undercount; Figure 3c) or too many (overcount; Figure 3d). More than one category could be assigned to a single image as it is possible for MegaDetector to both miss an animal and incorrectly assign the animal category to a non-animal. We labeled the camera data using the same categories that we applied to the video data. All validation of DeakinCams video segments and commercial camera trap images was performed by AJLP to maintain consistency. To establish whether MegaDetector provides a reasonable replacement for manual classification, we also recorded differences between manual classification and manual validation.

Evaluating performance

To evaluate the object detection results from both SAWIT and MegaDetector, we compared whether the categories assigned to each image through manual validation matched those assigned by the model to create four categories: true positive (TP), true negative (TN), false positive (FP), and false negative (FN) (Kohavi & Provost, 1998). The findings were then used to create confusion matrices using the "caret" (Kuhn, 2008) and "ConfusionTableR" (Hutson, 2021) packages in R 4.3.3 (R Core Team, 2024). Using ConfusionTableR, we extracted the performance metrics for each evaluation: Specificity (True negative), Sensitivity (True positive), Precision (proportion of correct positive predictions), Recall (comparison of the predicted positives to the total true positive rate), Balanced Accuracy (mean of Specificity plus Sensitivity), Accuracy (the proportion of all predicted results that are correct), Cohen's kappa (comparing the observed and expected accuracy), and the F score (the harmonic mean of Recall and Precision). Finally, for the binary confusion matrices, we calculated the Matthews correlation coefficient (MCC; Matthews, 1975) and its regression coefficients (Informedness, $\Delta p'$ and Markedness, Δp; Powers, 2011) for the multiclass confusion matrices. The MCC specifically assesses classification accuracy, while $\Delta p'$ and Δp refer to regression coefficients that describe relationships between predictors and outcomes (Powers, 2011). This can be beneficial in scenarios involving imbalanced classes in binary data (Powers, 2011).

We compared the manual classification results with the manual validation results for the Reconyx camera trap images using the same process. To evaluate the biological complementarity of the DeakinCams and Reconyx camera traps, we compared the taxonomic groups detected by each camera trap type.

RESULTS

Field deployment

We collected 85,870 individual video segments (>500 GB) from the DeakinCams and 50,888 images (>22 GB) from the Reconyx camera traps. This resulted in 83,005 DeakinCams videos and 44,000 camera trap images from 16 sites. The full DeakinCams dataset was used to test the SAWIT model. Given the volume of videos collected, we allocated 50 hours for RDS to manually classify a subset of them, resulting in 31,690 manually classified video segments (Table 1). All Reconyx camera trap images were manually classified.

SAWIT with DeakinCams

Manual classification of video segments yielded 809 animal detections and 338 test fire/human detections, including 363 detections of arthropods that the SAWIT model was not trained to recognize (i.e., arthropods other than spiders and scorpions) (Table 1). The arthropods that SAWIT could not detect and the human detections were excluded from further analysis, leaving 446 animal detections from 30,989 videos for data analysis. SAWIT identified 27,841 videos as animal detected, with the remaining 55,164 videos, from the full dataset of 83,005 videos, discarded as empty. Appendix S1: Figure S2 provides an example of the SAWIT output. Using the 31,690 manually labeled videos for comparison, SAWIT correctly identified 46% (14,295/30,543) of empty videos and 48% (212/446) of videos containing animals (Figure 4). This resulted in low specificity and sensitivity (0.47 and 0.48, respectively), and an F1 score of 0.67. The Matthews correlation coefficient (−0.01) indicates that the model performed slightly worse than random. Of the 212 true positives, the model correctly classified 35 (16.5%) to the right category (Figure 5), with the highest true positive classification for the *spider* category (19). The model did not correctly classify any *bird*, *scorpion*, or *small mammal* detections (Figure 5). Classifier model performance varied by category, with the *bird* category scoring the lowest for Informedness ($\Delta p'$; −0.450) and *snake* the highest (0.430), while Markedness Δp scores were centered around 0 except for *spider* (0.256) (Table 2). The high number of *bird* false positives (84.9%) was predominantly a result of the movement of either vegetation or the drift fence within the field of view.

MegaDetector with Reconyx camera traps

Manual validation of Reconyx camera-trap images resulted in 28,420 detections of 24 species, as well as 1424

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TABLE 1 Detection categories manually classified from DeakinCam videos and Reconyx camera trap images.

	DeakinCam		Camera trap	
Category	No.	Percentage of total	No.	Percentage of total
Bird	2	0.01	687	1.56
Empty	30,543	96.38	14,097	32.04
Frog	6	0.02	0	0
Human	338	1.07	1424	3.24
Large mammal	13	0.04	27,534	62.58
Large reptile	173	0.55	61	0.14
Scorpion	14	0.04	0	0
Small mammal	20	0.06	151	0.34
Small reptile	64	0.20	0	0
Snake	17	0.05	0	0
Spider	137	0.43	0	0
Unknown	363	1.15	46	0.10
Total	31,690		44,000	

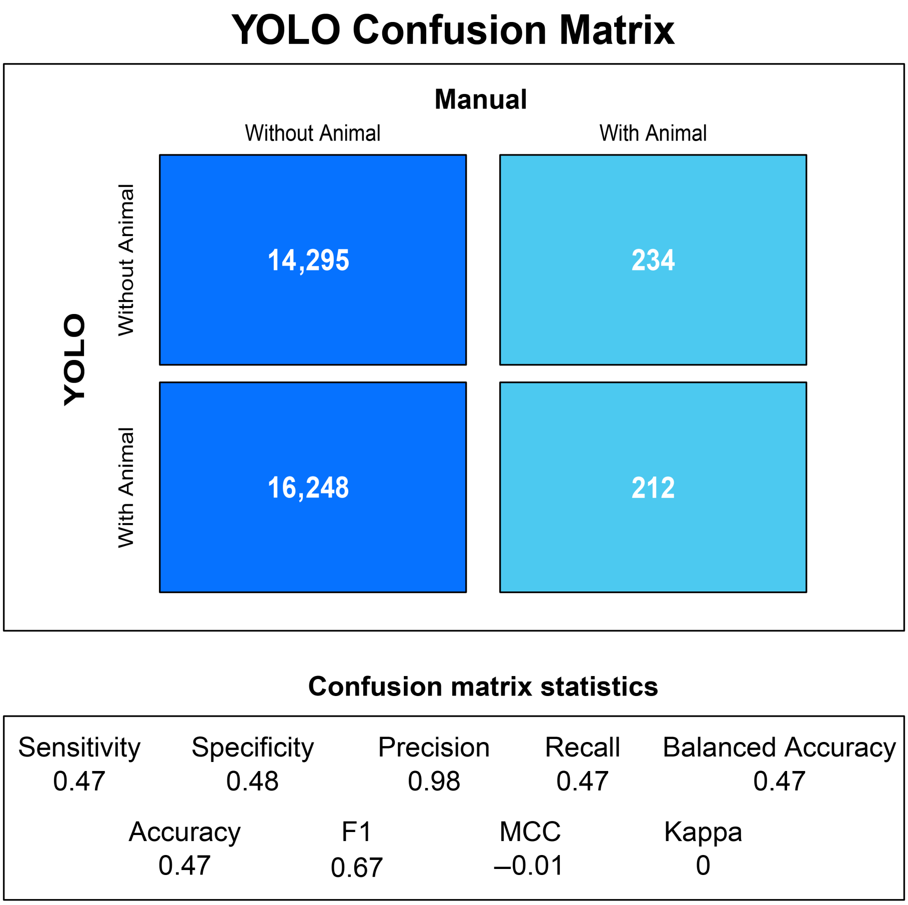

FIGURE 4 Confusion matrix of SAWIT object identifier detection of DeakinCams videos with model performance metrics. The top left represents the Specificity (true negative rate), top right represents the Type II error (false negative) rate, the bottom left represents the Type I error (false positive) rate, and the bottom right represents the Sensitivity (true positive) rate.

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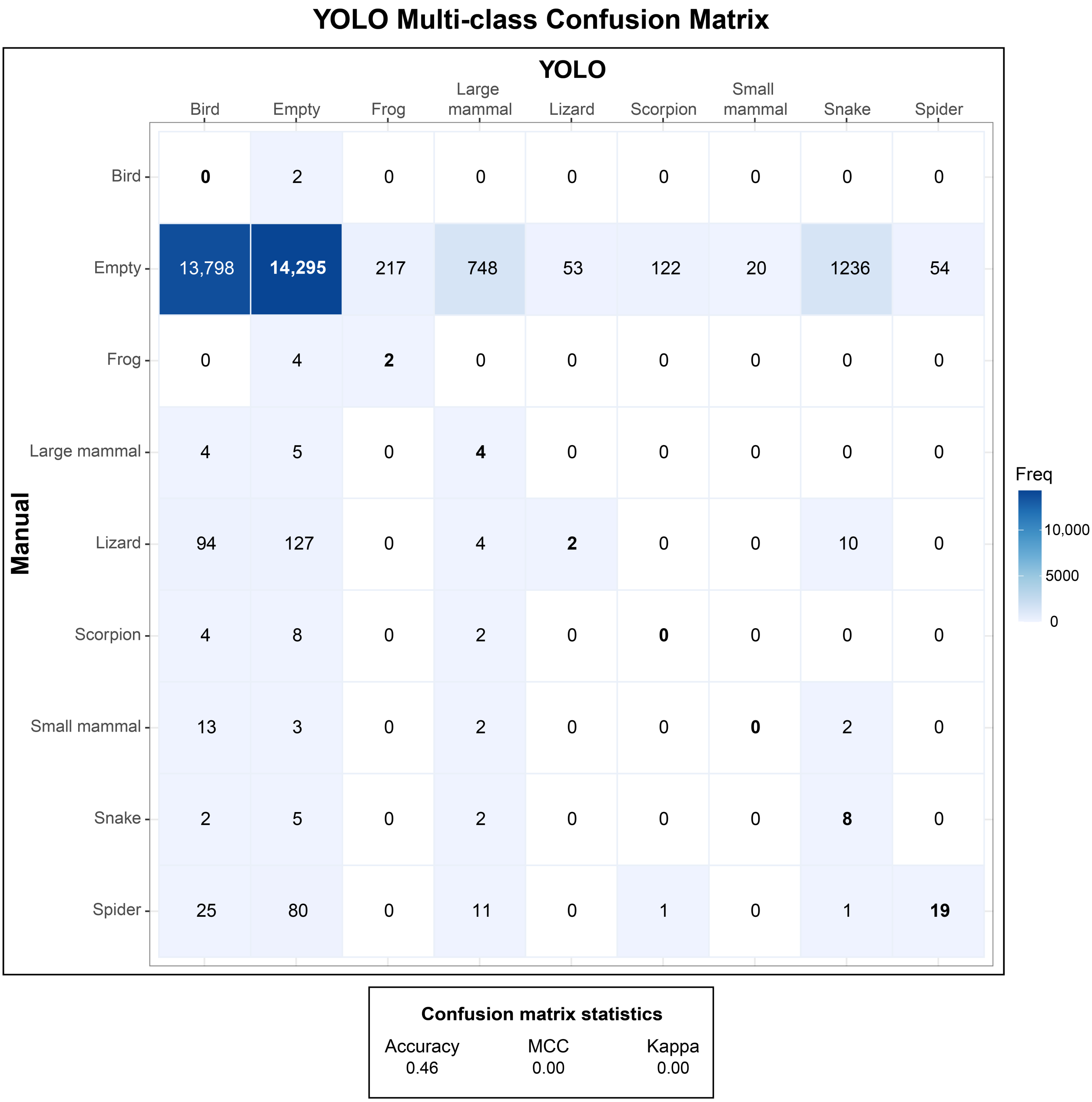

FIGURE 5 Multiclass confusion matrix of SAWIT object identifier classification of DeakinCams videos into the seven categories (plus empty) that the model was trained on compared with manual classification. Frequency of classification increases from white to dark blue.

images of people and 59 unidentifiable animal detections (Table 1), which were removed from further analysis, leaving 42,517 images. MegaDetector correctly identified animal images more than 99% of the time, with 192 (0.5%) false negatives and 255 (0.6%) false positives (Table 3). This resulted in high Precision (0.99), Recall (0.98), and Balanced Accuracy (0.99), with correspondingly high F1 (0.99) and MCC (0.98) scores (Figure 6). The highest number of errors for each error category (except false positives) was recorded for large mammals (Table 4; Figure 7), likely a reflection of the high number of detections of large mammals ($n = 27{,}536$) in the dataset. Most of the 126 false negative errors of large mammals were due to only a small part of the animal (such as the tail tip of a macropod) being present in the frame (Figure 8a) or the animal being obscured by vegetation (Figure 8b). The number of false positives differs by one between the validation categories and the confusion matrix because, in one image, an animal was missed (false negative) and vegetation was incorrectly assigned to the animal object category (a false positive), as shown in Table 4. This false true positive (sensu Leorna & Brinkman, 2022) was combined with false positives for analysis. Model performance was consistently high across

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TABLE 2 Summary of the SAWIT object identifier classification performance metrics for each category in the multiclass confusion matrix for the DeakinCams dataset.

Category	Sensitivity	Specificity	Precision	Recall	Balanced accuracy	$\Delta p'$	Δp
Bird	0.000	0.550	0.000	0.000	0.275	−0.450	0.000
Empty	0.468	0.475	0.984	0.468	0.472	−0.057	−0.003
Frog	0.333	0.993	0.009	0.333	0.663	0.326	0.009
Large mammal	0.308	0.975	0.005	0.308	0.641	0.283	0.005
Lizard	0.008	0.998	0.036	0.008	0.503	0.007	0.028
Scorpion	0.000	0.996	0.000	0.000	0.498	−0.004	0.000
Small mammal	0.000	0.999	0.000	0.000	0.500	−0.001	−0.001
Snake	0.471	0.960	0.006	0.471	0.715	0.430	0.006
Spider	0.139	0.998	0.260	0.139	0.568	0.137	0.256

Note: $\Delta p'$ represents Informedness and Δp represents Markedness.

TABLE 3 Validation categories for MegaDetector recognition data on Reconyx camera trap data, with error percentages.

	False negative		False positive		Undercount		Overcount	
Category	No.	Error (%)	No.	Error (%)	No.	Error (%)	No.	Error (%)
True	192	0.5	255	0.6	472	1.1	777	1.8
False	42,325	99.5	42,262	99.4	42,045	98.9	41,740	98.2
Total	42,517		42,517		42,517		42,517	

Note: False negatives occur when an animal was missed; false positives occur when an image does not contain an animal, but MegaDetector assigns the animal category. Undercount is when MegaDetector correctly detects animals but does not count all the individuals in the image; Overcount is when MegaDetector correctly detects an animal but counts too many individuals than are in the image.

the animal categories, with Informedness $\Delta p'$ and Markedness Δp scores all >0.9 (Table 5).

When validating the manual classification results for the Reconyx camera trap images, we found 61 (0.1%) false negatives and 72 (0.1%) false positives (Table 6; Figure 9). This resulted in very high Precision (1), Recall (0.99), and Balanced Accuracy (1), with very high F1 (1) and MCC (0.99) scores. In comparison, MegaDetector classification resulted in 192 false negatives and 255 false positives (Table 3, Figure 6). The false negatives in manual classification were related to the partial occlusion of animals within the images or the animals moving out of the field of view (Figure 8). The false positives are due to all images within a sequence being labeled the same irrespective of whether an animal was present within the image or not.

Comparing biological complementarity

The categories detected most frequently on the DeakinCams were *Empty* (96.38%), *Unknown* (1.51%), and *Human* (1.07%) while *Large Mammals* (62.58%), *Empty* (32.04%), and *Human* (3.24%) were recorded most frequently on Reconyx camera traps (Table 1). After removing *Unknown* and *Human* detections, *Empty* (98.56%), *Large Reptile* (0.56%), and *Spider* (0.44%) comprise the most detections by DeakinCams (Appendix S1: Table S1). Similarly, *Large Mammals* (64.74%), *Empty* (33.15%), and *Bird* (1.62%) were the most detected by Reconyx cameras after *Human* and *Unknown* detections were removed (Appendix S1: Table S1). A diversity of small ectotherms, including *Frogs* ($n = 6$), *Small Reptiles* ($n = 64$), *Spiders* ($n = 147$), and *Scorpions* ($n = 14$), were detected by the DeakinCams in contrast to the Reconyx cameras, with zero detections of these categories (Table 1).

DISCUSSION

Technological advances are urgently needed to increase the availability of data to assist environmental decision-making and conservation efforts (Silvestro et al., 2022). Technology can improve the speed and volume of data acquisition (Allan et al., 2018) and accelerate data processing time. This leads to results being incorporated into management recommendations faster (Fennell et al., 2022; Vélez et al., 2022). We collected a large volume

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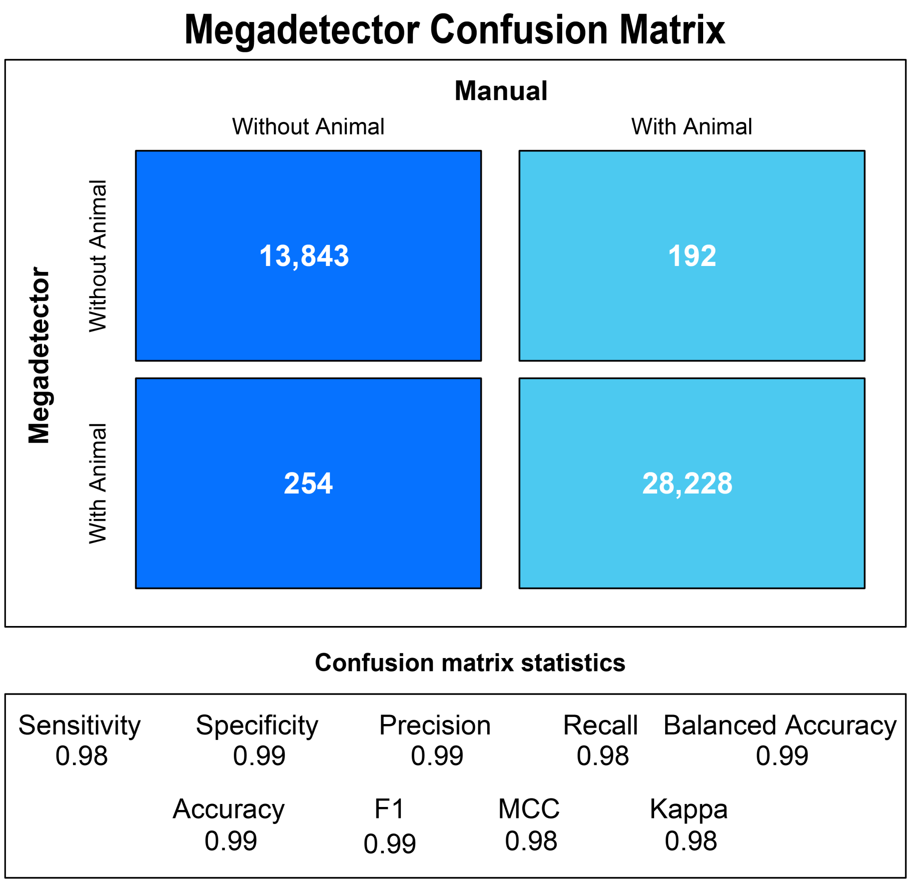

FIGURE 6 Confusion matrix of MegaDetector object identifier recognition of the Reconyx camera trap images. The top left count represents the Specificity (true negative) rate, top right represents the Type II error (false negative) rate, the bottom left represents the Type 1 error (false positive) rate, and the bottom right represents the Sensitivity (true positive) rate.

TABLE 4 Validation categories for MegaDetector recognition Reconyx camera trap data by image class.

	False negative		False positive		Undercount		Overcount	
Category	No.	Percentage of total	No.	Percentage of total	No.	Percentage of total	No.	Percentage of total
Bird	25	13	0	0	25	5.3	19	2.4
Empty	0	0	252	98.8	0	0	6	0.8
Large mammal	126	65.6	3	1.2	447	94.7	749	96.4
Large reptile	17	8.9	0	0	0	0	0	0
Small mammal	24	12.5	0	0	0	0	3	0.4
Total	192		255		472		777	

of data that, if processed manually, may have outweighed the advantages of gathering such information due to the associated costs and potential for human error (Figueroa et al., 2014). We consider the aim of automated data collection and classification should be for very high accuracy and precision compared with human validation, using data from any location. This enables species population trends of concern within ecosystems to be detected in as close to real-time as possible (Chalmers et al., 2023; Gomez Villa et al., 2017). Our results demonstrate that automation through computer vision has great potential for monitoring wildlife, but that further training is needed to improve the performance of existing models that are applied to ectothermic animals.

Field evaluation of DeakinCams

We found that despite some technical issues, the DeakinCams successfully recorded small fauna within

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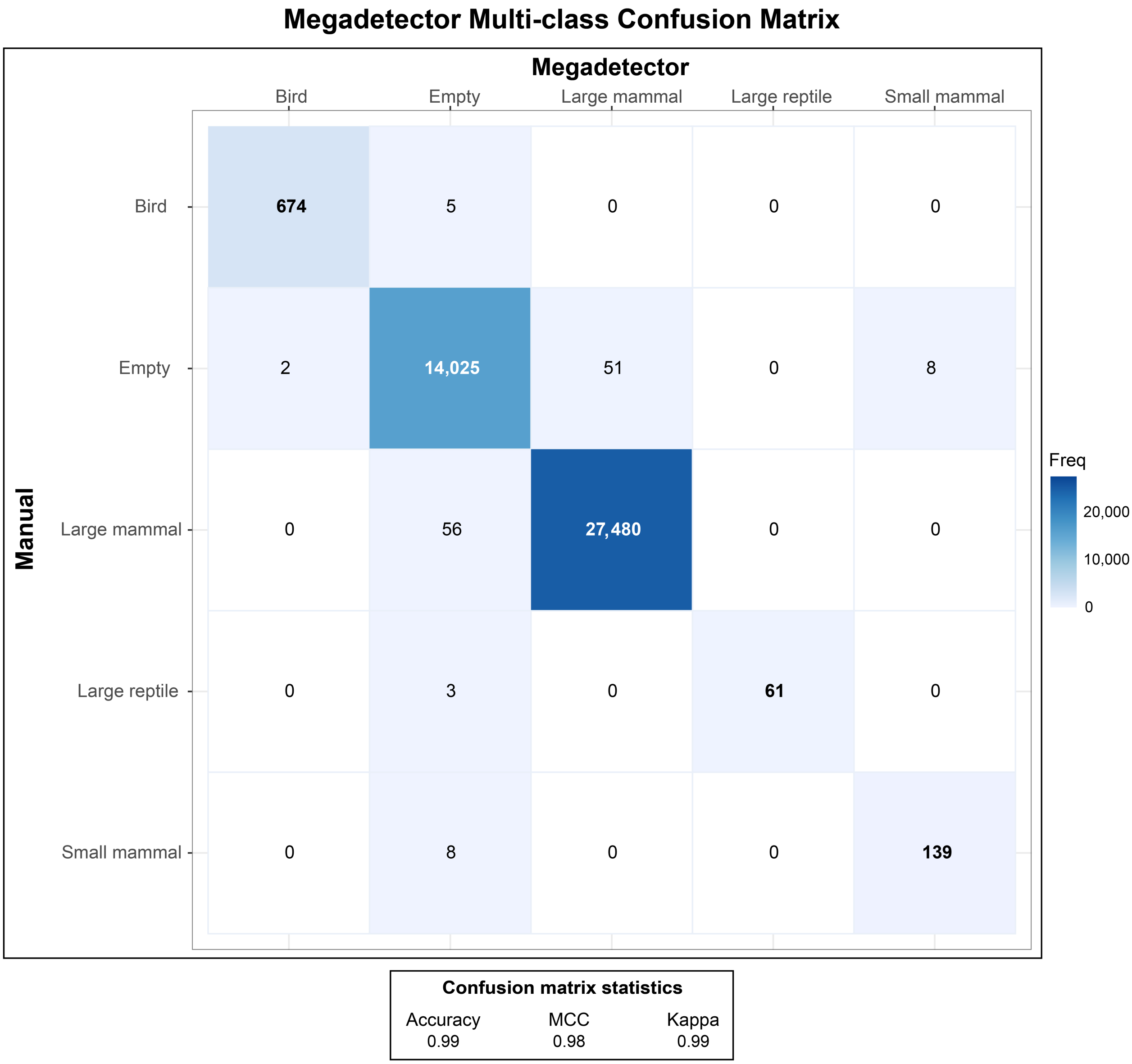

FIGURE 7 Multiclass confusion matrix of MegaDetector object identifier validation of the Reconyx camera trap images into the categories detected compared with manual classification. Frequency of correct classification increases from white to dark blue. We did not use MegaDetector to classify images, therefore this matrix represents whether MegaDetector's object identification output (Animal, Human, Vehicle) was correct when compared with the manually classified dataset.

the field of view, with over 800 detections manually classified from a subset of videos. This achievement was aided by the onboard foreground detection algorithm, which avoided the need for constant video, making data storage manageable. Indeed, camera traps with artificial intelligence capability are now used for monitoring invertebrate diversity in urban settings (Gao et al., 2024), agricultural invertebrate pests (Ding & Taylor, 2016; Kalamatianos et al., 2018), and invasive mammal species (Velasco-Montero et al., 2024). Future developments of DeakinCams that address the technical issues encountered could include faster processors, onboard AI for species identification, and real-time data communication. Combining onboard AI with a camera that is not triggered by movement has important implications for conservation, management, and research. In addition to reducing animal welfare issues, eliminating the need to trap animals means that the number of sites that can be surveyed is only limited by the number of cameras, not the amount of time it takes for daily checking of physical traps. Ultimately, this can lead to larger datasets for ectothermic taxa that are typically less often studied than mammals or birds.

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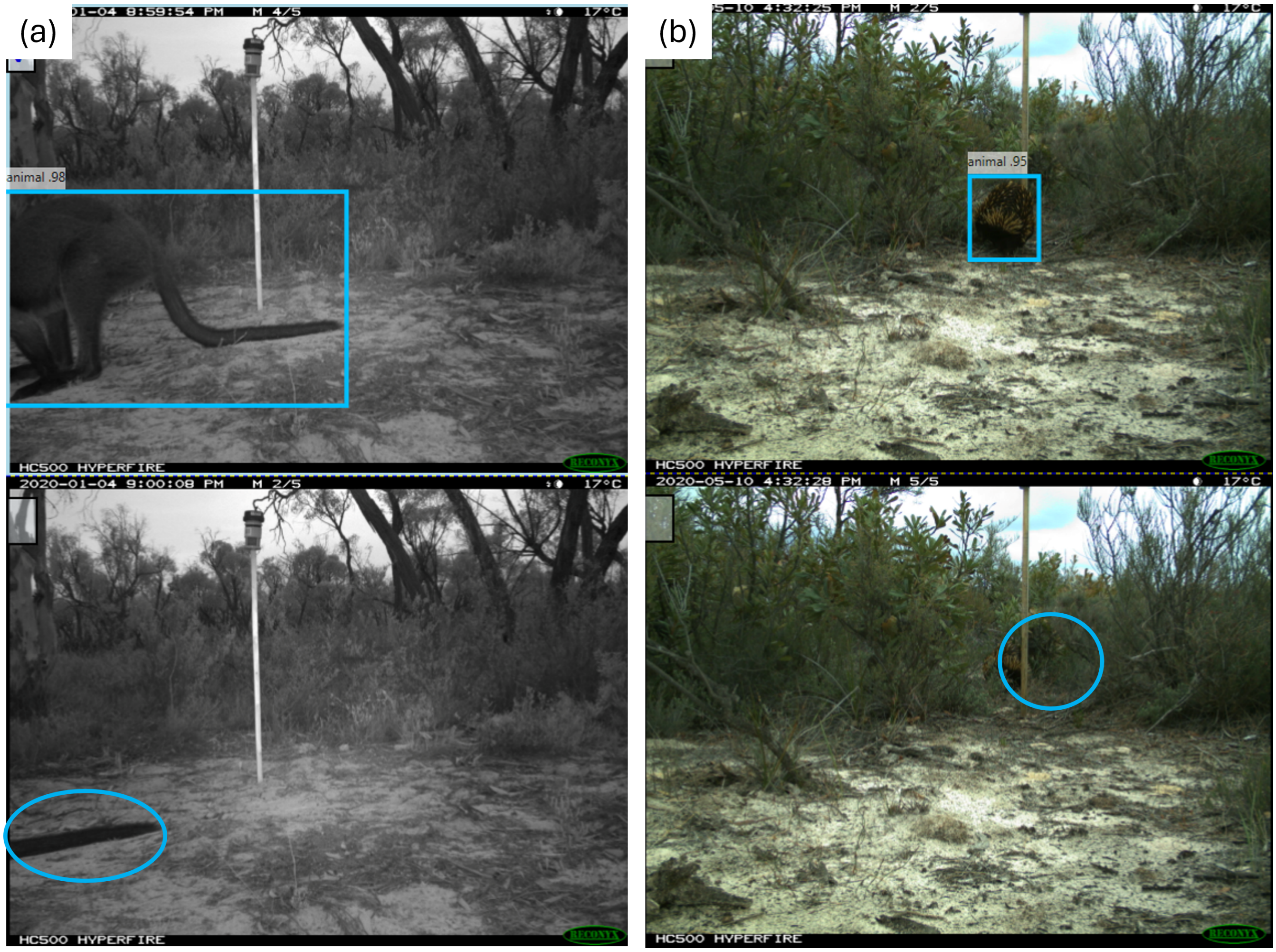

FIGURE 8 Examples of false negative errors where Megadetector has not detected an animal that has moved across the field of view of a Reconyx camera trap: (a) a black wallaby (*Wallabia bicolor*) is correctly detected (blue rectangle) in the top image but in the bottom image only the tail (blue circle) is visible but it was not detected; and (b) a short-beaked echidna (*Tachyglossus aculeatus acanthion*) is detected (blue rectangle) as it moves away from the field of view in the top image, but is not detected as it moves further away and is partially obscured by vegetation and the lure station stake (blue circle) in the bottom image. Photo credits: A. Pestell.

TABLE 5 Summary of MegaDetector performance metrics for each category in the multiclass confusion matrix for the Reconyx camera trap dataset.

Category	Sensitivity	Specificity	Precision	Recall	Balanced accuracy	$\Delta p'$	Δp
Bird	0.993	1.000	0.997	0.993	0.996	0.993	0.997
Empty	0.996	0.997	0.995	0.996	0.997	0.993	0.993
Large mammal	0.998	0.997	0.998	0.998	0.997	0.995	0.994
Large reptile	0.953	1.000	1.000	0.953	0.977	0.953	1.000
Small mammal	0.946	1.000	0.946	0.946	0.973	0.945	0.945

Note: $\Delta p'$ represents Informedness and Δp represents Markedness.

Current studies into invertebrates rely heavily on live sampling techniques and expert identification in the laboratory (Hoye et al., 2021). They are also taxonomically biased towards larger, more colorful species (Leandro et al., 2017). Given that some invertebrate taxa are capable of escaping from or avoiding traditional pitfall traps (Collett & Fisher, 2017), using smart traps such as the DeakinCams may be a suitable alternative. Unless a

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study requires species-specific or genetic material, for example, to differentiate morphologically similar species (Collett & Fisher, 2017), using camera traps may negate the need for live sampling for studies where the targeted taxa can be distinguished using video imagery. Camera trapping also facilitates in situ behavioral or observational studies that may have previously been costly or time-prohibitive (Collett & Fisher, 2017; Hoye et al., 2021).

TABLE 6 Validation categories for observer classification of Reconyx camera trap data, with error percentages.

	False negative		False positive	
Category	No.	Error (%)	No.	Error (%)
True	61	0.1	72	0.1
False	42,456	99.8	42,445	99.8
Total	42,517		42,517	

Note: False negatives occur when an animal was missed by the observer; false positives occur when an image does not contain an animal, but the observer assigns the animal category.

SAWIT with DeakinCams

Despite the advantages the DeakinCams provided, we needed to exclude almost half of the manually classified invertebrate detections from our analysis because the SAWIT model was not trained to detect and identify them. Many of the videos labeled as empty by the SAWIT model included invertebrates that did not correspond to the animal categories used in training the dataset (Nguyen et al., 2023). This is a common limitation with deep learning models, which have ostensibly limited their utility beyond the training environment (Schneider et al., 2023). Using the default confidence threshold instead of calibrating the model to find the optimal confidence threshold also limited the generalizability of the model (Dussert et al., 2024). Retraining the model by reclassifying the data to include all animals visible in the videos and calibrating with different confidence thresholds may improve our understanding of how well the model works for classifying animals. Given the taxonomic biases in current invertebrate research (Leandro et al., 2017), resolving this disparity has implications for reducing such biases in future research.

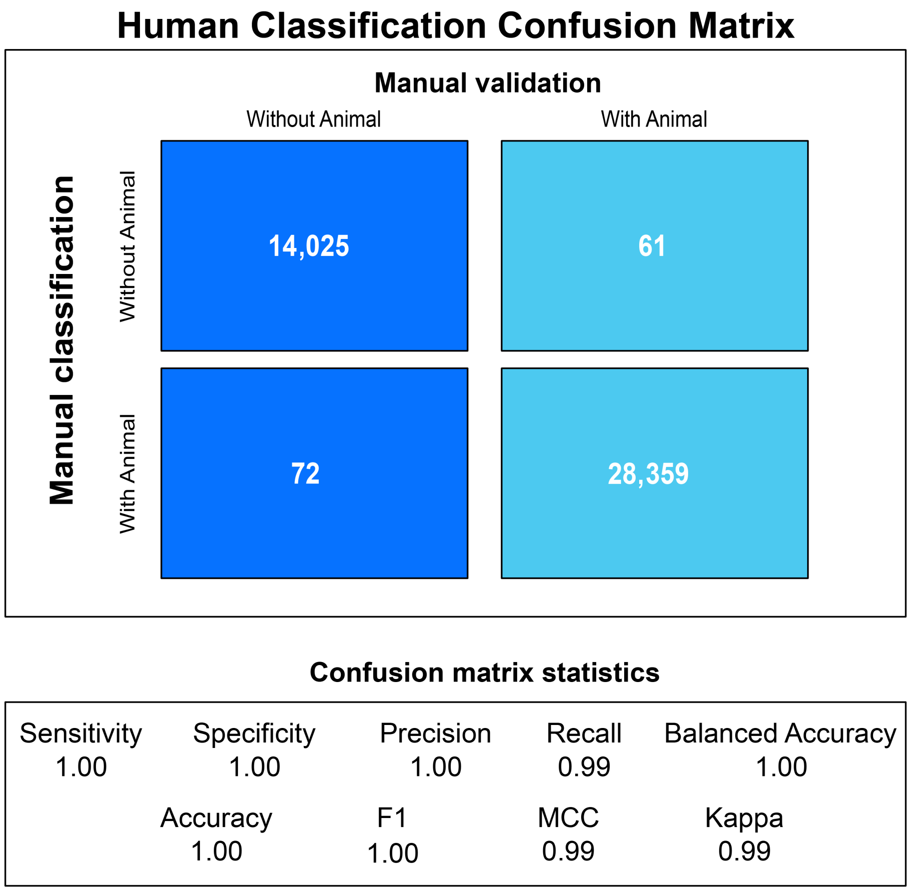

FIGURE 9 Confusion matrix of human classification of animal images. The top left count represents the Specificity (true negative rate), top right represents the Type II error (false negative) rate, the bottom left represents the Type 1 error (false positive) rate, and the bottom right represents the Sensitivity (true positive rate).

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Background interference and partial or total occlusion of the field of view were common causes of false positives in our study. This has been observed in other datasets (Chalmers et al., 2023; Gomez Villa et al., 2017), including another study using the DeakinCams (Nguyen et al., 2023). In our study, we also observed that shadows, rainfall, vegetation, and movement of the drift fence within the field of view triggered false detections by the onboard CPU. When false positives from our data were screened through SAWIT, they were incorrectly classified as *birds* (Figure 5). Resolving such issues would require iterations of training and testing of the model with new locations (Miao et al., 2021). The perceived time and expertise to do so may, however, act as a deterrent for many researchers with limits on either time, expertise, or both (Beery, Morris, Yang, Simon, et al., 2019; Desprez et al., 2023). With the rapid use of computer vision tools employed in ecological studies in the past decade (Pichler & Hartig, 2023), there are opportunities to use a real-time object detection and classification algorithm with a more powerful onboard processor (e.g., Chalmers et al., 2023; Tuia et al., 2022). This would further reduce the level of manual processing. Indeed, Nazir and Kaleem (2024) have recently demonstrated the use of transfer learning and explainable AI to perform onboard image classification on a novel, Raspberry Pi-based camera trap, achieving performance metrics comparable to the MegaDetector results reported herein.

MegaDetector with Reconyx camera traps

While manual classification resulted in a lower rate of false positives (0.1% or 72 images) than MegaDetector (0.6% or 255 images), we found that MegaDetector was extremely accurate (>99%) at separating images of animals from "blank" images in our study ecosystem. MegaDetector can therefore substantially reduce the manual classification process (e.g., Bohnett et al., 2023). In the context of the expected time savings of using MegaDetector to automate object labeling, such a low rate of false positives generated by MegaDetector is insignificant. This is particularly so given that all the manually classified false positives resulted from labeling entire detection sequences as containing an animal. We have found that this is a common practice in camera trap image processing (Pestell et al., 2024) and while it may be useful for some purposes, it is not good practice for assessing the performance of machine learning models.

Similarly, false negatives represented just 0.5% (192 images) of the MegaDetector results, with large reptiles representing 8.9% (17 images) of these errors. While these taxa are commonly under-detected by remote-sensing cameras (Corva et al., 2022; Welbourne et al., 2019), the higher error rate here is likely associated with poor training data compounded by poor detection probability. Given that large reptiles were under-represented in the Reconyx camera trap (61 images at 0.14% of the total), and smaller ectotherms were not detected at all, resolving the detectability of ectotherms is important. The use of more targeted camera setups (i.e., downward-facing cameras with a shorter field of view and no IR-trigger such as the DeakinCams) for these groups is required (Welbourne et al., 2019) to ensure that adequate datasets are available for training object detection models.

Context around false negatives can be valuable when considering their relative impact. A false negative that is one image of a species in a sequence of five images taken in a burst, where the animal was successfully detected in the rest of the sequence, will have negligible impact. For example, the false negatives in manual classification comprised just 0.1% (61 images), with large mammals being the most common (51/61, 84%). In most cases, these false negatives were a single image within a sequence, and the animal was detected in the other sequence images. False negatives like this often occurred when only very small parts of the large mammal were visible (i.e., the end of the tail of the animal; Figure 8). As such, these errors did not result in animals being missed entirely. However, models that do not detect an animal in an entire sequence of images pose a problem for researchers and land managers, which could arise through inadequate data for training. This is particularly the case for studies involving cryptic or rare species (Bohnett et al., 2023) or when as close to real-time detection as possible of an invasive species is critical for preventing incursions (e.g., Kalamatianos et al., 2018; Smith et al., 2024). Artificial intelligence methods are rapidly evolving (Nakagawa et al., 2023). For example, since the initiation of this research, developments have been made with MegaDetector (Hernandez et al., 2024) and its integration with Timelapse (Greenberg, 2025) to move towards automated species classification using the EcoAssist tool (van Lunteren, 2023). Although not ready for true automation yet, preliminary results hold substantial promise (A. Pestell, unpublished data). This is especially the case in scenarios where labeled photos from previous camera work at the same site can be used as training data specific to the study system (van Lunteren, 2023).

Evaluating performance

We found that both object detection models were successful at finding animals in camera trap data and that MegaDetector performed just as well as manual

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classification. However, our results also demonstrate that some manual processing is necessary to validate model outputs, with the level of human intervention varying by model selection. The comparatively poor performance of SAWIT on our data supports prior observations that models trained on a single location are not easily transferable to others (Beery et al., 2018; Eichholtzer, 2024). In our case, we used the same YOLOv5 (Redmon & Farhadi, 2017) model trained and tested on the SAWIT dataset (Nguyen et al., 2023), with Eichholtzer (2024) achieving high (0.96) accuracy compared with our low (0.47) accuracy, despite both studies using the DeakinCams. These results highlight the need for computer vision models to be generalizable across locations if they are to be widely adopted (Beery et al., 2021). The high performance of MegaDetector in our and other studies (for example Fennell et al., 2022; Vélez et al., 2022) is largely a result of the underlying model being iteratively trained on camera trap data from across the world (Beery, Morris, & Yang, 2019), exposing the algorithm to new backgrounds and species. We caution, however, that we did not use the separate MegaDetector classification model (Microsoft AI for Earth, 2018) on our data, so our inferences are based on the detection capabilities of the model only.

The MegaDetector model used herein is an object detector that screens for animal presence or absence and assigns a confidence value for the prediction. MegaDetector outputs can then be viewed in a graphical user interface (GUI) such as Timelapse (Greenberg & Godin, 2015) for validation. This is a relatively simple process for identifying potential false negatives and may be conducted at the same time as other validation processes ("human-in-the-loop" processes; Käding et al., 2016). By contrast, the SAWIT model (Nguyen et al., 2023) is an object classifier that excludes empty videos from the classification task without manual oversight. This has the potential to produce false negatives, which are then discarded without manual processing.

For this study, manually processing the 31,690 video segments used in our analysis took 50 h; at ~633 video segments per hour, this equates to 136 h to process all 85,870 segments. This is a conservative estimate and is based on a single person who was familiar with the task. Evidence suggests that the quality and accuracy of manual annotation vary from person to person (Chan et al., 2023; Zett et al., 2022). Incorporating object detection and classification models can significantly improve the processing speed of camera trap data (Chan et al., 2023; Fennell et al., 2022). We therefore suggest that the SAWIT model be further developed to decouple the tasks of detection and classification and incorporate a human-in-the-loop process to validate outputs at both stages (Bodesheim et al., 2022). This approach has successfully been deployed on other taxa in a variety of ecosystems (e.g., Bodesheim et al., 2022; Kulits et al., 2021) as well as on video footage of animals from the internet (Käding et al., 2016). Calibration of the model with multiple confidence thresholds after further training may also lead to improvements in model performance (Dussert et al., 2024). These refinements should minimize the risk of false negatives leading to missed detections as well as decrease the need for extensive manual processing post-classification while maintaining a level of human oversight.

Biological complementarity

Standard camera traps rely on heat-in-motion passive infrared sensors to detect fauna, which has resulted in a trend toward detections of medium- and large-bodied endotherms (Corva et al., 2022; Delisle et al., 2021). Efforts to reduce this trend include changes to camera trap setup such as trap orientation (Moore et al., 2020), using specific models (Brown et al., 2023), and modifying programming aspects (Welbourne et al., 2019). The DeakinCams were designed to address the existing data gap for small fauna (Corva et al., 2022; Nguyen et al., 2023). Our results demonstrate that the DeakinCams were successful in detecting a range of ectotherms that were not detected by the Reconyx camera traps (Table 1). Indeed, by also detecting medium-sized fauna, they have performed above expectations in that regard. DeakinCams, therefore, can help to fill the gap left by commercial camera traps, enabling insights into small and ectothermic animals. In combination with commercial camera traps (e.g., Eichholtzer, 2024), more complete coverage of vertebrates can be achieved.

Applications and future advances of smart cameras

In a recent survey of conservation practitioners, researchers, and technologists, Hahn et al. (2022) identified that the automation of camera trap image processing was a priority in the conservation technology sector. Our results on machine learning for object detection and classification should provide practitioners with the confidence to use existing technologies to automate their camera trap processing methods. Indeed, our results have already led to changes in existing processes within some land management organizations (e.g., Pestell et al., 2024). However, we recognize that for some taxa, such as threatened species, there is little to no margin for error and

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manual validation will be necessary (Bohnett et al., 2023). We therefore concur with recent calls advocating that continued manual validation processes be retained in automation processes to mitigate known issues such as poor generalization of models to novel scenes and species (Bodesheim et al., 2022; Chan et al., 2023). Having a full dataset classified rather than limiting labeling to a single species or suite of target species would provide greater opportunities for researchers to contribute to and share data for studies at multiple spatial and temporal scales (Young et al., 2018). Collaborative efforts across nations and continents are critical to further global efforts to monitor biodiversity and inform conservation policies (Bruce et al., 2025; Young et al., 2018).

Our DeakinCams used an AI motion detection algorithm to detect movement across the field of view, enabling the storage of videos of a range of taxa for post-processing with machine learning tools. With continued efforts to adapt new machine vision approaches like transfer learning (Bodesheim et al., 2022) into the DeakinCams and integrating an onboard species classifier, they offer great potential for the future study of small and difficult-to-survey fauna. Although not tested in our study, the DeakinCams are equipped with climate sensors, GPS, and a microphone (Corva et al., 2022) that would enable a wider range of data to be collected, particularly bioacoustics. These additional sensors could be used to identify species not detected otherwise using machine vision (Stowell, 2022). The potential of the internet of things (IoT) and "smart environments," as envisioned by Allan et al. (2018), could see remote or sensitive ecosystems monitored via a series of connected devices that are able to transmit data either in real time or at regular intervals. These types of multisensor platforms would enable a whole-of-landscape approach to biodiversity monitoring that will enhance conservation efforts while reducing costs (Lahoz-Monfort & Magrath, 2021). Our study adds to the growing evidence of the benefits of using technology and machine learning to aid conservation efforts.

AUTHOR CONTRIBUTIONS

Don A. Driscoll, Duc T. Nguyen, and Abbas Z. Kouzani conceived of and designed the customized smart camera traps. Angela J. L. Pestell, Don A. Driscoll, and Euan G. Ritchie designed the methodology in consultation with Dean M. Corva, Duc T. Nguyen, and Abbas Z. Kouzani. Angela J. L. Pestell collected the data; Angela J. L. Pestell, Robin D. Sinclair, and Anne C. Eichholtzer processed the data; Angela J. L. Pestell and A. R. Rendall analyzed the data and led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data and code (Pestell, 2024a, 2024b; Nguyen, 2025) are available from Zenodo: DeakinCams: https://doi.org/10.5281/zenodo.13340369; SAWIT Dataset: https://doi.org/10.5281/zenodo.14927692.

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